TASK-CV: Transferring and Adapting Source Knowledge in Computer Vision
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Incremental Domain Adaptation of Deformable Part-based Models*

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http://www.cvc.uab.es/domainadaptation/

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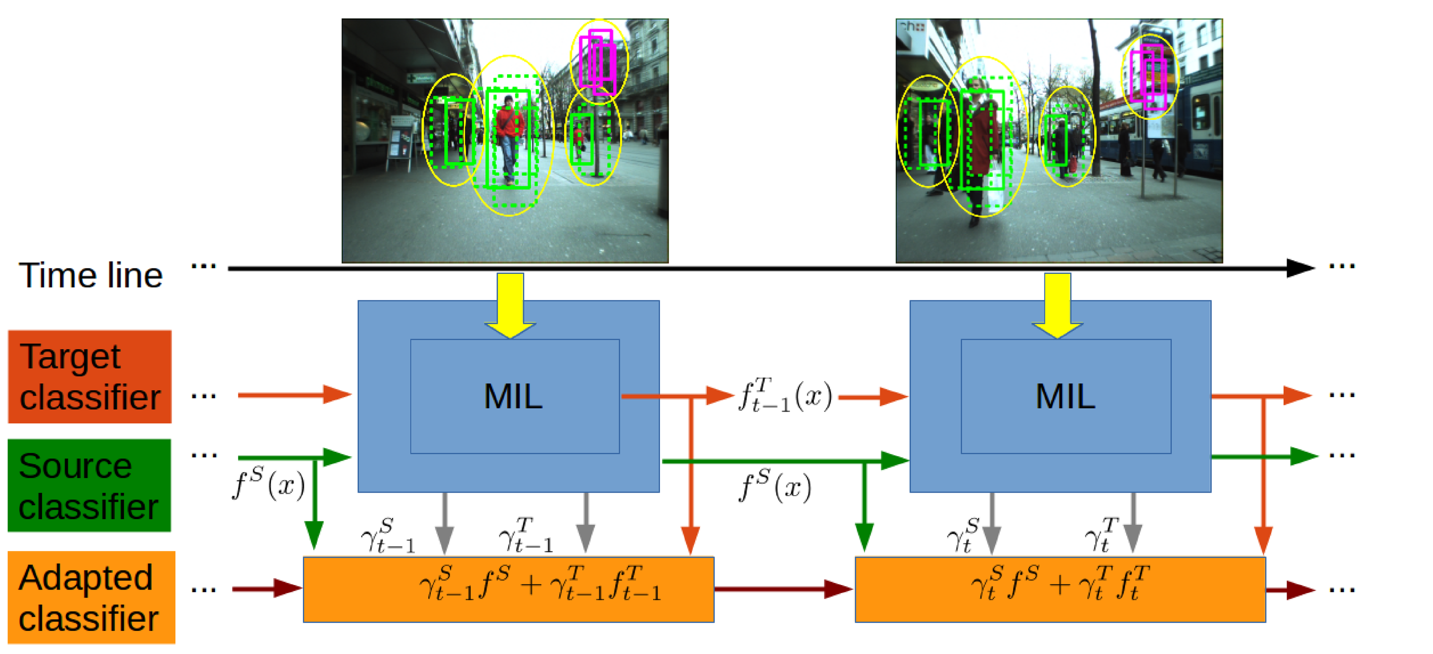
ABSTRACT

In this work we focus on the domain adaptation of deformable part-based models (DPMs) for object detection [1]. In particular, we focus on a relatively unexplored scenario, i.e. incremental domain adaptation for object detection assuming weak-labeling. Therefore, our algorithm is ready to improve existing source-oriented DPM-based detectors as soon as a little amount of labeled target-domain training data is available, and keeps improving as more of such data arrives in a continuous fashion. For achieving this, we follow a multiple instance learning (MIL) paradigm that operates in an incremental per-image basis. As proof of concept, we address the challenging scenario of adapting a DPM-based pedestrian detector trained with synthetic pedestrians [2, 3] to operate in real-world scenarios.

PROPOSED APPROACH



Incremental domain adaptation framework. $f_t^T(x)$ is the classifier trained in a multiple instance learning (MIL) manual with current target image, while the final target-domain adapted classifier is: $\gamma_t^S f^S(x) + \gamma_t^T f_t^T(x)$

Online Transfer Learning (OTL):

$$f^E(\mathbf{x}) = \gamma_t^S f^S(\mathbf{x}) + \gamma_t^T f_t^T(\mathbf{x}),$$

$$\gamma_{t+1}^S = \frac{\gamma_t^S g_t(f^S)}{\gamma_t^S g_t(f^S) + \gamma_t^T g_t(f_t^T)}, \quad \gamma_{t+1}^T = \frac{\gamma_t^T g_t(f_t^T)}{\gamma_t^S g_t(f^S) + \gamma_t^T g_t(f_t^T)}$$

$$g_t(f) = \frac{1}{M_t} \Sigma_{i=0}^{M_t} \exp\{-\frac{1}{2} l^*(\Pi(f(\mathbf{x}_i)), \Pi(y_i))\},$$

$$\Pi(s) = \max(0, \min(1, \frac{s+1}{2})) \quad l^*(\bar{y}, y) = (\bar{y} - y)^2$$

Incremental Multiple Instance Learning:

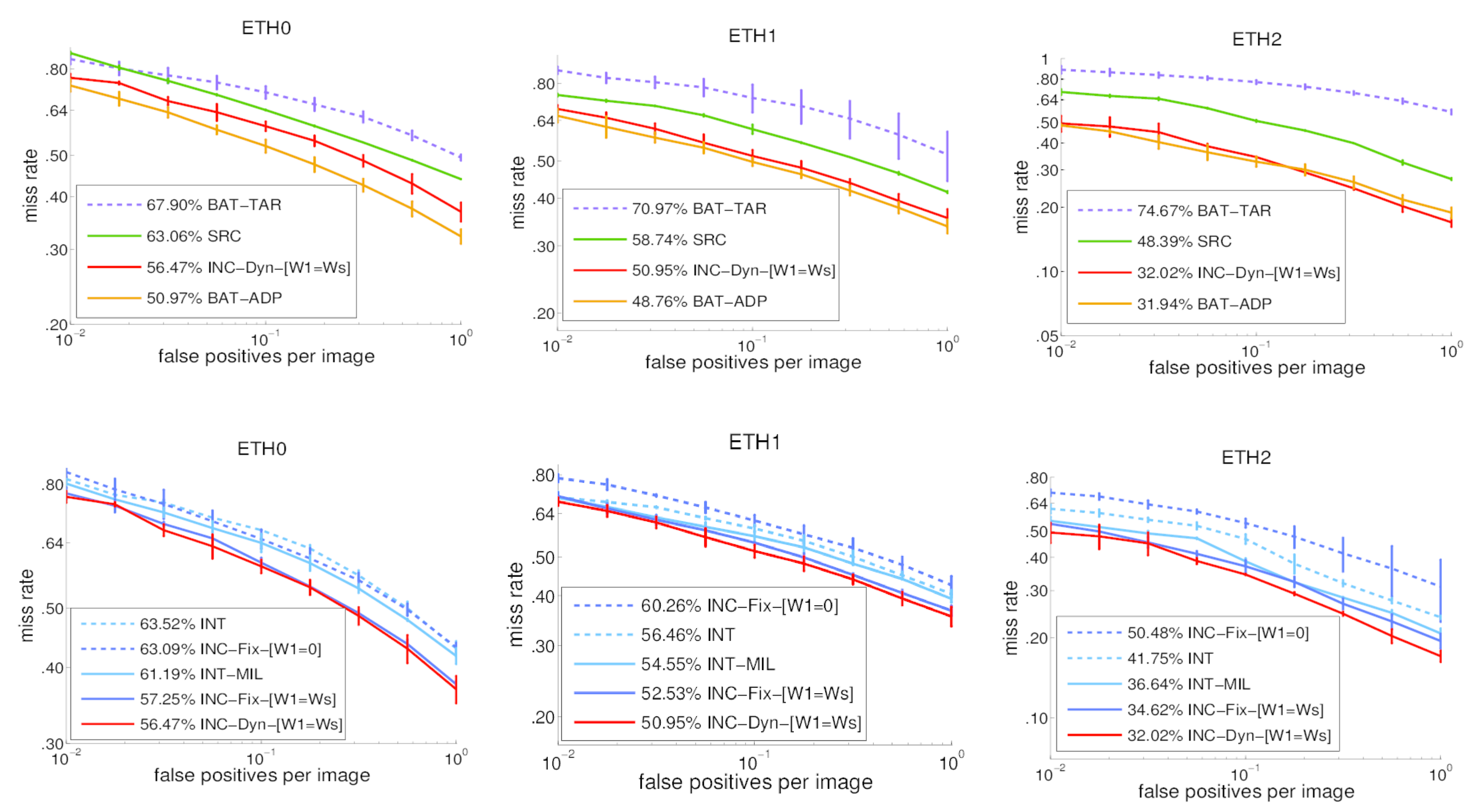
$$f_t^T(\mathbf{x}) = f_{t-1}^T(\mathbf{x}) + \Delta f_t^T(\mathbf{x}),$$

$$J(\mathbf{w}_t) = \frac{1}{2}\|\mathbf{w}_t - \mathbf{w}_{t-1}\|^2 + C \sum_{i=1}^{N_t} \mathcal{L}_{surr}(\mathbf{w}_t, \mathbf{x}_i, y_i, \mathbf{h}_i).$$

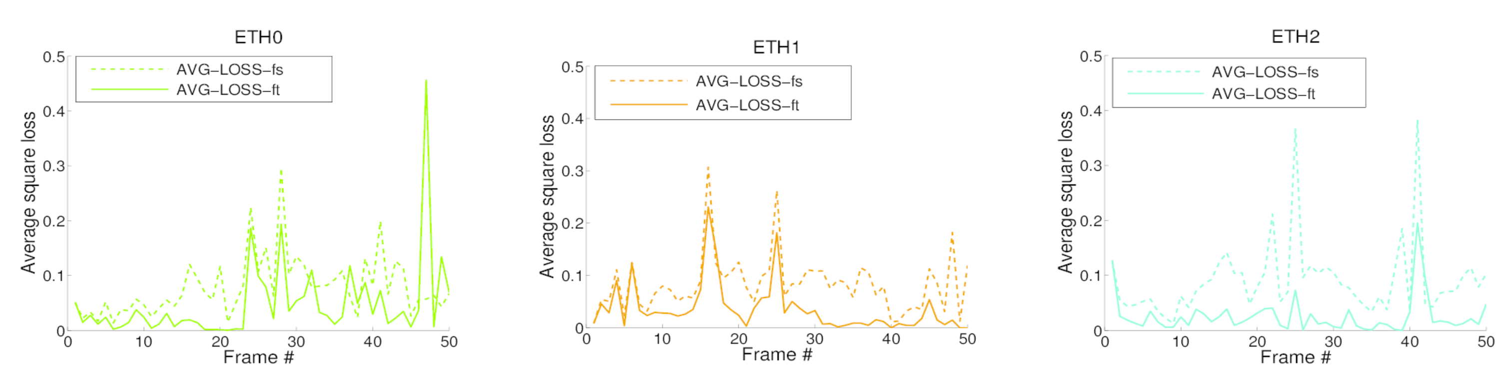
Algorithm Incremental Domain Adaptation

Input: source classifier: f^S, target-domain training images: $\{I_t, t \in [1, N]\}$,
coefficients: $\gamma_1^S = \gamma_1^T = 0.5$.
Output: $f^E = \gamma_N^S f^S + \gamma_N^T f_N^T$
0: $f_1^T \leftarrow f^S$
1: **for** t=1,2, ..., N, **do**
2: Receive image I_t, collect samples $\mathcal{D} = \{(\mathbf{x}_i, y_i, \mathbf{h}_i)\}$.
3: Predict the labels of the samples in $\mathcal{D}$ by f^S and f_t^T.
4: Compute γ_t^S and γ_t^T by OTL
5: Generate training bags.
6: Learn f_{t+1}^T with the collected bags
7: **end for**

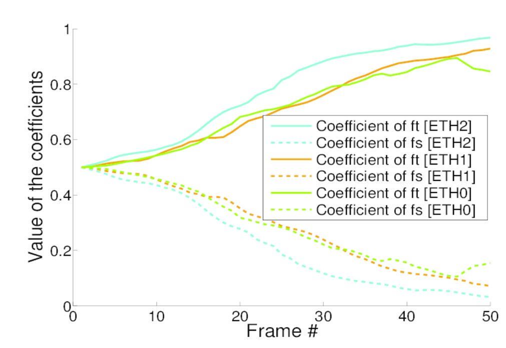
EXPERIMENTAL RESULTS



Results of adapting a DPM pedestrian detector trained with synthetic images to operate in ETH pedestrian dataset.



Average square loss of the source and target classifier in each iteration.



The Coefficient (r_t^S, r_t^T) changes at each iteration

REFERENCES

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[4] J. Xu, S. Ramos, D. Vázquez, A. M. López. Incremental Domain Adaptation of Deformable Part-based Models. BMVC, 2014.